Forecasting Economic Growth with the Hungarian Composite Stock Market Index – a Granger Causality Test

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Abstract: The relationship between the stock market and the economy, for developed markets, has been subjected to scrutiny, in the field of economic forecasting, since the late 90s. This research revisits the concept, the methodology and the findings of previous works and presents a new updated algorithm of testing the relationship between the economy and the stock market of a developing economy. Following a rigorous examination of the stock markets' strengths and shortfalls in predicting the economy, supported by the efficient market hypothesis, this paper presents the methodology for evaluating the BUX Hungarian composite stock market indicator as a leading indicator of economic growth. The quarterly data from the BUX is traced back to the second quarter of 1995 effectively providing 86 observations spanning across 26 years. Through the application of the ADF and the KPSS tests it is further determined in the work that the data is indeed mean reverting and independent of the time domain, and therefore, stationary. The coefficients of the autoregressive distributed lag model are further determined in the work through running an OLS regression test. It is determined that changes in the Hungarian GDP directly affect the immediate changes in the BUX composite stock index in a predictable way. The results of the Granger causality test, further strengthen the argument of the BUX being an important leading indicator, of the Hungarian economy.

Keywords: economic growth; stock market; leading indicators; composite stock market index; efficient market hypothesis; johansen cointegration test; stationarity testing; autoregressive distributed lag model; granger causality

1 Introduction

Leading indicators are known to be incredibly useful in predicting future economic conditions. The field of economic forecasting and econometrics is oversaturated with multidimensional factor models, shrinkage methods, linear forecasting models, loss functions and variations of the Bayesian approach. Nevertheless, it can be stated with a high degree of certainty that none of the aforementioned are particularly widely used among economists for forecasting crises or predicting cycle changes in the economy. Many forecasts derived from observing and modelling leading indicators, at best, represent an oversimplified reality, where causal relations between economic variables are seldom identified, if at all, and where models of financial time series are used by central banks and other financial institutions as tracking tools and back testing.

The choice of the stock market as a leading indicator is supported by the scoring system of Moore and Shiskyn [1], who built upon the previous research of Mitchell and Burns [2]. The selection criteria are divided into (i) economic significance in relation to business cycles; (ii) statistical adequacy of the data; (iii) conformity to historical business cycles; (iv) consistency of timing during business cycles; (v) smoothness; (vi) currency. In the stock market criterion (i) is reflected in the decreases and increases of stock prices. While the former is reflective of a future recession, the latter indicates economic growth – an expansionary period in the economy, according to Commincioli [3]. The (ii) criterion concerns statistical adequacy of the collected data. The stock market provides a rich source of data, the time delay of which is often neglected. Because of the high frequency of the stock market data generation process, a statistically significant number of observations can be attained in a relatively short period of time. Criterion (iii) states that there has to be a conformity to business cycles – reflected in the literature as a quantifiable simultaneous replication of the smoothness of the business cycles with the large fluctuations of the stock market variable [4]. The findings of Adam and Merkel show that 'boom-bust cycles' happen in clusters, which means that there is a positive correlation between the stock market and the economy. Other studies related to the development of a composite leading indicator, recently increasing in popularity among potential predictors of economic activity, have further supported the argument that the stock market is a valuable leading indicator [5]. The (iv) property concerns economic significance – how direct is the relationship between the leading indicator and the economy. The market value of a company reflected in the share price represents not only investor confidence, but also potentially higher revenues – an indicator that consumers are spending more, thus contributing to the GDP, hence the relationship. The smoother a time series is, following criteria (v), the more accurately it signals the change of cycles in the economic sector. No economic time series meets the criteria of being perfectly smooth because of short-term volatility, the effect of which can be significantly reduced through 'data cleaning' procedures, detailed in section three. Following Moore and Shiskyn, smoothing (v) and currency (vi) should be considered in relation to one another. Currency relates to the frequency of the release of the data. In case of the stock market, depending on individual stocks, the value of share prices changes multiple times in a second – all driven by supply and demand, buyers and sellers.

Following the theoretical reasons as to why the stock market might be a good leading indicator compiled in section two, the research assesses whether the stock market leads the real economy[1], as in Comincioli's work.

The objective of the research is to evaluate the composite stock index of Hungary (BUX) as a leading indicator of economic activity in the country through a multi-step algorithm developed by the author that involves: (i) building a regression model of the GDP on past values of BUX composite stock market index; (ii) determining its coefficients; (iii) testing for cointegration, and finally, (iv) performing the Granger causality test, which allows to determine whether past values of the BUX index are useful in predicting the future values of the GDP with a higher degree of accuracy, than by using past values of the GDP.

The rest of the research is organized the following way. The literature review presents the efficient market hypothesis, its critics and supporters. Further on the stock market's recession predicting capabilities are evaluated through a pro-con analysis. In the third section, the methodology is presented and detailed in an algorithm, the models are presented, and the mathematical background of further tests is explained. The fourth section features the reasoning behind the choice of data warehouses and presents the data. In section five the results of the application of the algorithm to the data are presented and interpreted. In section six the results of the empirical research are further discussed, and section seven provides meaningful conclusions.

2 Literature Review

2.1 A Review of the Efficient Market Hypothesis

The generally accepted definition of Efficient Market Hypothesis (EMH) is that incoming market information is instantaneously incorporated into the price of stocks. Technological progress has allowed the information spread to achieve never-before seen paces and spread. Price discovery is the process of market information being incorporated into the price of the stock. The nature of news, its flow and distribution, however, is inherently unpredictable. Therefore, the association of this process with the statistical term of "random walk" defined in Fama [6] groundbreaking work is appropriate. Following the updated definition of Malkiel [7], a capital market is considered efficient if it fully reflects the relevant information in market prices, and if the security prices remain unaffected by the disclosure of new information to market participants. Fama uses the Ω_t information

[1] The concept of the stock market leading the economy is derived from Comincioli's research [3], where the variation in the stock markets past values explains the variation in the economy.

set to define the forms of EMH – weak, semi-strong and strong. The EMH does not rule out predictable patterns, instead studies identify them as anomalies. The most frequent anomalies are exploited by simple trading strategies. Lo [8] identifies the "January effect", calendar effects, short-term interest rates, price-to-earnings multiples and the value line enigma as the most frequently identified patterns that are considered anomalies by the EMH.

Critics of the EMH, in particular [9] argue that efficient markets are an impossibility, since there would be no advantage to gathering information, and therefore, no reason to trade.

As a supporting argument for the EMH, an article by Sotiroff [10] showed that over a 10-year span, less than half of actively managed funds were able of beating the market.

To settle the question of whether markets could really be deemed efficient, we turn to Malkiel, who argues that in an efficient market serial correlation among stock prices should be zero, due to the random and independent nature of incoming news. Studies of Fama, Poterba and Summers [11] show that serial correlations exist, and they are positive, thus disproving EMH. Malkiel, however remarks that though, the findings of the aforementioned authors are statistically significant, they may not be economically significant. When publishing finings of anomalies in finance literature, the market seems to instantaneously incorporate it into the price of a stock, thus, eliminating the anomaly.

There have been many policy measures enacted by governments to prevent financial crises from happening and to avert the growth of corporations to the extent of them becoming too essential for the system. The Basel III accord raised banks' minimum capital requirement and risk exposure, set a backstop leverage ratio and introduced liquidity requirements – thus tightening the regulation of the financial sector on an international level. Early Warning Systems (EWSs) have been introduced by European monetary institutions to monitor macroeconomic imbalances across member states. Within the EWS framework Alert mechanism reports (AMRs) are issued on a quarterly basis, where the top macroeconomic risks are highlighted for each member state. The method on which the authors of the AMR predict which sector is the most vulnerable to a crisis or which specific macroeconomic indicator would produce the most accurate signal is based on the signal method first introduced by [12]. The stock market has been regarded as the chief leading indicator for the economy – and therefore, a good predictor. However, the statistical framework built around the topic is, in our opinion, outdated and should be subject to review and scrupulous analysis. Therefore, we adapt and update the methods introduced in Comincioli's paper, for determining the relationship between the stock market and the economy.

2.2 Stock Markets' Ability to Predict Recessions – Evidence

Stock markets are closely related to economic cycles, which is a long-term pattern of alternating periods of economic expansions and declines – known as the business cycle. Stock prices reflect investor' expectations about profitability, and since economic activity is driven by profitability, it is believed that investors will anticipate a recession by selling stocks and rotating into safer assets. In the traditional stock price valuation model, the price of the stock is its present value of expected future returns. Following this logic, stock prices fall as soon as the near-term expectations of corporate profits decline, and comparatively, a higher rate used to discount future earnings results in stock prices going lower. A higher discount rate usually means the rise of uncertainty and volatility in markets. Leading macroeconomic indicators, such as consumer sentiments, housing construction starts, industrial production tends to move ahead of the economy. Investment strategies are rarely based on market behavior in the past. Instead, investment strategies are built around thorough company performance research, the analysis of valuations and predicting future earnings.

The question of the stock market's ability to predict recessions has been examined since the early 60's. Nobel-Prize winning economist Paul Samuelson was the first to publish his findings – 5 out of the 9 recessions that occurred up until 1966 were predicted by bear markets. According to a recent article Samuelson's remark was right on. In the postwar period, there have been 13 bear markets. Out of the 13 bear markets 7 led to recessions within a year [13]. Chen [14] provides further evidence of the predictive power of the stock market through analyzing illiquidity – the measure of how easily a security is exchanged on the market. They have found that the annual change in stock market illiquidity is a strong predictor of the economy. The dynamic probit models classify 70% of the recessions.

In the early 70s financial literature, the stock market has been studied for its effect on consumer demand. Bosworth [15] links the stock markets macroeconomic forecasting ability to a number of mechanisms: (1) investor optimism pessimism, also known as consumer sentiment, and (2) the life-cycle model of consumer behavior. To determine whether the stock market is a good leading indicator, Bosworth proposes examining the nature of the correlation between changes in stock prices and consumption to find whether monetary policy affects stock prices. This correlation could represent a wealth effect or a proxy for consumer sentiment.

The wealth effect is also regarded as a major supporting argument for the forecasting ability of stock markets. Following the definition provided by the national bureau of economic research, the wealth effect is the idea that as asset values grow, such as company stock prices or home values, households would spend more and stimulate the economy – thus creating a positively reinforcement loop. Pearce [16] defined the wealth effect in terms of a consumer sentiment. Again, adopting the element of risk into the theoretical framework, Pearce points out that when investors are optimistic, this is reflected in a higher level of confidence in markets, lower volatility, higher returns and eventual economic expansion. On the other hand, if stock prices are declining, investors are less optimistic, less wealthy and more likely to put their money into 'safer' assets.

2.3 Stock Markets' Inability to Predict Recessions – Evidence

Practical evidence, however, shows that the stock market is a poor indicator of future economic activity. Since the stock market generates many "false signals" that are usually hard to interpret. Comincioli mentions the 1987 "Black Monday" stock market crash, that triggered a global selloff, as one of these events, when stock prices falsely predicted the economy. In a publication by Kaverman [17] it is established that markets are generally irrational – this is expressed in market anomalies, such as Dot-com bubble, the housing bubble and even the latest cryptocurrency bubble. Irrational market behavior isn't only induced by endogenous factors involving the fear of missing out, speculation and panic, but also by exogenous factors, independent of the sentiment or action of market participants. Injection of stimulus into the banking system, lowering interest rates, quantitative easing – all of these exogenous factors contribute to the markets becoming more irrational.

Another key reason why the stock markets' recession forecasting abilities are subject to criticism is connected with investors' expectations. Often investors' expectations about future economic activity are inherently flawed, biased and simply incorrect. Human error, after all, plays a great deal in both price discovery and making predictions on future corporate earnings. The ability to make well-informed predictions and investment decisions is often hindered by the level of optimism or pessimism in the market – hence, Keynes' [18] definition of investors as "spirit animals". Neither optimism nor pessimism can be identified in market momentum as a good predictor of the economy. Stock prices rise or fall due to the reinforcement of the expectations of investors. The perceived state of confidence or distrust in the system will drive investors to either take up more risk by investing in high-yielding assets like stocks and derivatives or save their money by investing in low-yielding assets, like government bonds. As a result, the argument of anticipation of higher or lower corporate earnings doesn't hold any longer in the process of price discovery – thereby the market becomes irrational, unpredictable, and the stock market will not be a useful leading indicator, according to Pearce.

3 Material and Method

This study evaluates the composite stock market index of Hungary by empirically testing for causality and cointegration, similarly to Sayed [19], Ikoku [20], and Comincioli. The literature review has put forward the idea that even though the flow of information is unpredictable, and hence, so are market movements, nonetheless, anomalies exist, and they can be defined within a statistical framework. The analysis of evidence and counterevidence to stock markets' ability to predict recession has shown that stock markets do not always cause changes in the real economy, and the extent of their impact and influence on the economy is often determined by the state of the domestic markets and development of the country's financial system. In order to ascertain if there exists a relationship between stock prices and the economy the Granger-causality test is implemented.

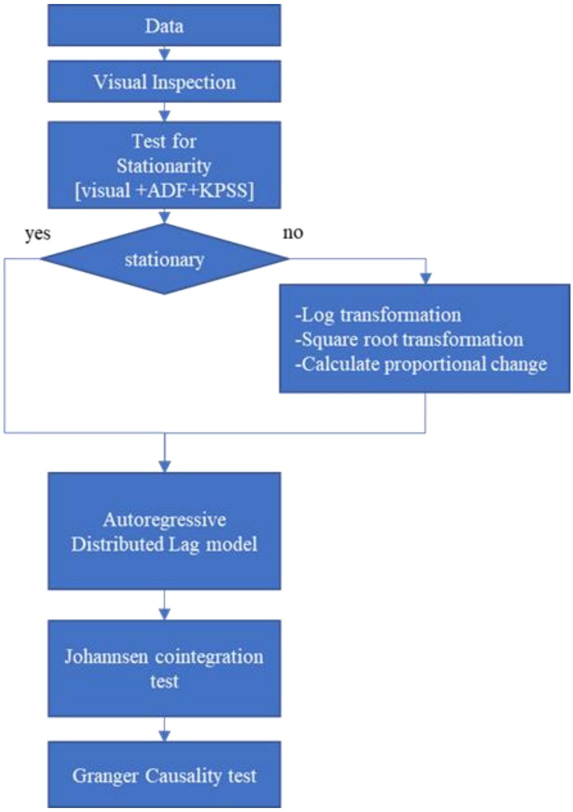

Figure 1
Algorithm of the test

Source: Own compilation

In Figure 1 we define the complete algorithm for determining the relationship between the stock market and the economy including all of the necessary tests and statistical inferences and assumptions we make along the way. The data on the variables have been collected over a period of 26 years, totaling 86 observations depending on the availability of data. Most of the empirical works on economic data have been conducted under the assumption that the time series are stationary. For all intents and purposes in this research we consider a stationary stochastic process, whereby the time series will tend to revert to its mean as time progresses. To determine whether the time series are stationary, we compute the Augmented

Dickey Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test as a means of getting two independent answers. A more detailed explanation of stationarity and its testing methodologies is provided in the subsequent chapters of this research.

In case the time series is found to be nonstationary, most of the literature recommends transforming the data by differencing processes. In this study, however, we consider the log-transformation process, as we believe that it is more efficient in removing skewness and hence, making the time series stationary – mean reverting according to Hassler [21].

In our research we suggest that there is a relationship between the economy and the stock market. The autoregressive distributed lag model (ARDL), which is a model based on the ordinary least square regression applicable for both stationary and nonstationary data. The model is useful for separating long-run relationships from short-run between two-time series. The ARDL is also significantly less vulnerable to spurious regression, it provides a flexible method for incorporating different lag structures.

Making statistical inferences based on the results of the Granger causality test without proving that the time series are integrated would not be ample in econometrics, therefore we regress the GDP percentage change for Hungary to the composite stock index of the country back 4 quarters. The number of lags, in our case – 4, has been chosen because fewer lags will lead to avoiding the relevant variable bias. Choosing any more would result in inclusion of irrelevant variable bias. The Akaike information criterion computed in Python provides the optimum number of lags.

$$GDP = \alpha + \beta_0 StockMarket_t + \beta_1 StockMarket_{t-1} + \ldots + \beta_4 StockMarket_{t-4} \qquad (1)$$

According to Weierstrass' theorem, on a finite closed interval any continuous function may be approximated uniformly by a polynomial of a suitable degree. After running the regression based on equation 1, we may find, for instance, that β_1 is statistically significant, while β_2 isn't. In this case we assume that the first degree polynomial provides a reasonable approximation.

Having determined the coefficients of the regression and having asserted their significance, we move further along the algorithm and proceed to the Johansen cointegration test. The Johansen test, otherwise referred to the maximum eigenvalue or the trace test is a likelihood ratio test. It enables us to determine the relationships between two or more nonstationary time series. Regressing nonstationary time series on other nonstationary time series results in a spurious regression. Within the scope of our research cointegration refers to the following: (i) there exists a long-term equilibrium between Hungary's GDPs and the BUX stock market index, (ii) Hungary's GDP and the BUX index move in a way, so that their linear combination results in stationarity, and (iii) the time series share a common stochastic trend.

In line with the above defined theoretical framework, we investigate the forecasting ability of the stock index and the GDP.

As it was mentioned before, the Johansen cointegration test outputs two statistics: the trace statistic, which is a likelihood ratio function that sequentially tests the null hypothesis that the Π matrix, which is the number of cointegrating vectors, is equal to its rank r (Equation 2).

$$\begin{aligned} &1. H_0: r_0 = (\Pi)\ ; \quad H_a: r_0 < (\Pi) \\ &2. H_0: r_0 + 1 = (\Pi); \quad H_a: r_0 + 1 < (\Pi) \\ &\vdots \\ &\vdots \\ &N. H_0: r_0 + N = (\Pi); \quad H_a: r_0 + N < (\Pi) \end{aligned} \tag{2}$$

The trace test is thereby calculated by the following likelihood ratio:

$$LR(r_o, n) = -T \sum_{i=r_o+1}^{n} \ln(1 - \lambda_i) \tag{3}$$

where T is the sample size λ is the largest eigenvalue.

A non-zero vector, that, when subjected to a linear transformation, changes by a scalar factor is an eigenvalue. The maximum eigenvalue test evaluates if there is a cointegration between the time series. For this, we define the following two hypotheses and their corresponding alternatives:

$$1. \quad H_0: (\Pi) = 0; \quad H_a: (\Pi) = 1 \tag{4}$$

If the null hypothesis is confirmed, meaning the rank of the Π matrix is zero, therefore we conclude that the largest eigenvalue is zero, hence we conclude that no cointegration exists between the time series whatsoever. Conversely, if the alternative hypothesis is confirmed, meaning that the largest eigenvalue λ_1 is nonzero, and the rank of the Π matrix is equal to or more than one, we conclude that there is at least one cointegrating vector, and hence the second null hypothesis can be further defined. We test the following set of hypotheses:

$$\begin{aligned} &1. H_0: \lambda_2 = 0\ ; \quad H_a: \lambda_2 > 0) \\ &\vdots \\ &\vdots \\ &N. H_0: \lambda_n = 0; \quad H_a: \lambda_n > 0 \end{aligned} \tag{5}$$

If the first largest eigenvalue λ_1 is nonzero, we further test whether λ_2 is nonzero up until λ_n, where we will be able to confirm the null hypothesis.

The eigenvalue test is a likelihood ratio test denoted as follows:

$$LR(r_o, r_o + 1) = -T\ln(1 - \lambda_{r_o+1}) \tag{6}$$

It is important to note that neither of the test statistics follow a chi square distribution. In case the time series contain a unit root, or in other words, is stationary, the critical values of the maximum eigenvalue and the trace test will be incorrect [22]. However, since the appropriate tests for stationarity are already predefined in the model, we are free to neglect the statement. From the "statsmodels.tsa.vector_ar.vecm" python library we import the "coint_johansen" test to produce more assertive and reliable results. The results are detailed in the corresponding chapter of the research

The idea of causality has been introduced by Norbert Wiener in 1956, who inferred that a time series is causal if the ability to predict another time series is improved by the incorporation of information about the former [23]. In his seminal work Granger [24] dissects the two-variable feedback mechanism into causal relations. Granger defines causality as the predictability of some series. If information contained in the past values of Y_t time series effectively predicts values of X_t time series and the extent of this predictability can be measured, then Y_t is said to cause X_t. A purely nonstationary deterministic time series can't have causal influences other than autocorrelation or auto-covariance. This is the reason why stochasticity is important in the Granger-causality test. Instead of measuring causality as a positive relationship between an event and an outcome, Granger views them as precedents of information. Diebold [25] asserts that the Granger-causality test is a test for predictive causality. Following Granger's notation, if U is all of the information accumulated since time $t-1$, causality is defined as $\sigma^2(X|U) < \sigma^2(X|\overline{U-Y})$, where Y is causing X. The Granger-causality test further ascertains if adding the lagged values of X_t would improve the predictive power of the Y_t time series. Further description of the Granger causality test and its interpretation can be found in the Granger causality section of this research.

In this study we shall examine the question if the Hungarian stock market actually causes the changes in Hungarian GDP (Stock market → GDP), where the arrow points to the causality's direction.

$$GDP = \sum_{i=1}^{n} \alpha_i StockMarket_{t-i} + \sum_{i=1}^{n} \beta_j GDP_{t-i} + u_{1t} \tag{7}$$

$$StockMarket = \sum_{i=1}^{n} \lambda_i GDP_{t-i} + \sum_{i=1}^{n} \delta_j StockMarket_{t-i} + u_{2t} \tag{8}$$

To perform the Granger Causality test it is necessary to estimate the regression defined in equations 7 and 8. Both equations state that the time series are related to the past values of themselves in addition to being related to the past values of the other time series. Gujarati [26] defines three different cases based on the results of the test: (i) unidirectional causality – when the values of the lagged *StockMarket* variable are not zero, and when the values of the lagged *GDP* variable are zero; (ii) bilateral causality – an outcome, when the coefficients in equations 7 and 8 are not zero; (iii) independence – suggested when the coefficients in equations 7 and 8 are statistically insignificant.

Before we define the algorithm of the Granger causality test, we must first list the prerequisites and make some assumptions, namely: (i) the time series are stationary; (ii) the choice of the number of lags is defined by the Akaike information criterion; (iii) The error terms are uncorrelated.

To test the causality between the *StockMarket* and *GDP* time series as well as the direction of the causality equations 7 and 8 have been specified. Following Gujarati, the steps in testing if the stock market causes changes in the economy are the following:

1) A restricted regression is performed solely on the *GDP* time series, where we regress the current *GDP* on its own lagged values excluding lagged *StockMarket* variables in the regression. From the results of the regression, we obtain the restricted residual sum of squares RSS_R
2) We perform an unrestricted regression, where we include the lagged *StockMarket* variables. From the results of the regression, we obtain the unrestricted residual sum of squares RSS_{UR}
3) We declare the null hypothesis, which is the following: $H_0 : \sum \alpha_i = 0$. The hypothesis states that lagged StockMarket variables do not belong in the regression, and therefore are unsuitable to predict the economy
4) To test the hypothesis, we perform the F test given by equation 9, where m is the number of lagged StockMarket terms, and $n - k$ refers to the degrees of freedom

$$F = \frac{\frac{(RSS_R - RSS_{UR})}{m}}{\frac{RSS_{UR}}{n-k}} \tag{9}$$

5) Finally, having obtained the value of the F- statistic, we compare it to the critical value at the 95% significance level. If the F- statistic is greater than the critical value, we reject H_0.

Of course, it must be mentioned that the results, which are based on the algorithm in Figure 1, presented in the following chapter, must be considered as suggestive rather than absolute, as previous works of Comincioli, Ikoku and Sayed suggest that the Granger causality methodology is one surrounded by controversy.

4 Preparing the Data

The macroeconomic data for the research have been obtained from three large data libraries: the imf.data.org, the European central bank statistical warehouse, and the Eurostat database. The BUX time series were retrieved from the MarketWatch and Yahoo Finance databases. While retrieving the data, we paid special attention to seasonal and trend adjustment. Further analysis of non-transformed data would have resulted in spurious statistical inferences. Taking into account the ramifications of unadjusted stock index data, we applied the following transformation : $S_t = \frac{P_t - P_{t-1}}{P_t}$. A log-transformation expressed as $S_t = \ln(P_t) - \ln(P_{t-1})$ yields similar results, and it removes the skewness of the data. A log transformation, however, must be conducted keeping in mind that it also makes the interpretation of the results of a multiple regression more complicated. Among other advantages log transformation reduces the variability of data and makes patterns more visible [27]. We used the quarterly percentage change of the Gross Domestic Product (GDP) as the variable measuring changes in real economic activity.

In the below table we have illustrated the normalized values of the Hungarian GDP (HUGDP) and the national stock index log returns (BUX).

	HUGDP	BUX
0	-0.001281	0.191267
1	0.000307	0.092816
2	-0.004319	-0.042006
3	0.005388	0.600587
4	-0.005563	0.343715
...	...	...
82	-0.006414	0.105782
83	0.014172	-0.004742
84	0.004675	0.050850
85	0.008833	0.156838
86	0.014700	-0.011523

Figure 2

Hungary’s GDP and Stock index log-transformation

Source: Own compilation

In order to perform the Granger causality test, both of the time series need to be of the same frequency. Since the GDP data are released on a quarterly basis, the stock prices needed to be adjusted to the corresponding frequency. As a result, we have filtered the stock data by quarters and extracted the closing values. Most of the data span from 1995Q3 to 2021Q2 totaling around 84 – 100 observations. It is also worth mentioning that the BUX stock index is value-weighted.

5 Results

5.1 Testing for Stationarity

Following the definition of Gujarati, a stochastic time series is considered stationary if its mean and variance are constant, and its covariance depends solely on the lag between the observations. If a time series would be nonstationary, any statistical inferences made about the time series would only be correct for the studied time period. It would be impossible to generalize the findings and therefore, the model would be of little use.

Making statistical inferences on data containing trend, random walk or seasonality will result in faulty conclusions. The time series must therefore be tested for the presence of a unit root that makes it nonstationary. Phillips [28] notes that errors present in the univariate time series can't be reliably modelled by independence or homoskedasticity and therefore, can't be characterized as random walk. In a stationary time, series, the mean, variance and autocorrelation don't change over time.

For the sake of simplicity, in this paper we will be testing the time series for stationarity with the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. If the aforementioned tests yield the same results, we will be confident enough to proceed with the next steps of the algorithm. Each test has its own specific advantage and field of application. The augmented dickey-fuller test removes autocorrelation from the series and tests for stationarity similarly to the dickey-fuller test, first proposed in the seminal work of Dickey and Fuller [29]. The unit root test is carried out under the null hypothesis H_o = the series has a unit root. The dickey fuller test creates a t-statistic, which is compared to critical values, allowing us to affirm or reject the null hypothesis. Following [30] the ADF is based on: $y_t = \alpha + \rho y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t$, where α is a constant, β is the time coefficient and p is the lag order of the autoregressive process, and e_t is noise. If $\rho = 1$, then, the null hypothesis holds which means the time series contains a unit root. To reject the null hypothesis and declare the time series stationary, the p-value must be less than the significance level. The ADF test is able to handle complex models, however, it does have a high Type I error rate.

In the program listing, following the syntaxes defined in 'statsmodels.tsa.stattools' we set the regression to constant and trend, set the auto lag to the Aikaike information criterion (AIC) and run the test.

```
result = adfuller(series, regression ='ct', autolag='AIC')
```

Table 1

ADF tests of BUX and Hungarian GDP time series

ADF Statistic: -9.603763 p-value: 0.000000 Critical Values: 1%: -4.049 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary	ADF Statistic: -11.508826 p-value: 0.000000 Critical Values: 1%: -4.050 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary

Source: Authors research and own compilation

Table 1 displays the results of the ADF test conducted on log returns of the composite stock indexes of Hungary (BUX). In all of the cases the log-returns of the stock index have proven to be successful in eliminating stationarity and thereby enabling us to proceed with the analysis. The ADF statistic in all of the cases is lower than all of the critical values – this further strengthens the decision of rejecting the null-hypothesis. Furthermore, the rejection of the null hypothesis is also justified by the extremely small p-value.

However, in order to confirm our findings, we should perform an alternative test - the KPSS test. The null hypothesis in the KPSS test is that the data is stationary, while the alternative hypothesis is that the time series is not stationary. By rejecting the alternative hypothesis, we can't assume the time series is stationary, we must also consider trend-stationarity. The data of our research were tuned for the KPSS test, so that the no exponential trends would interfere with the results.

Table 2

KPSS test of Hungarian BUX and GDP time series

KPSS Statistic: 0.3622484501988779 p-value: 0.09342739215565607 num lags: 2 Critical Values: 10%: 0.347 5%: 0.463 2.5%: 0.574 1%: 0.739 Result: The series is stationary	KPSS Statistic: 0.11436010799191071 p-value: 0.1 num lags: 4 Critical Values: 10%: 0.347 5%: 0.463 2.5%: 0.574 1%: 0.739 Result: The series is stationary

Source: Authors research and own compilation

In their pioneering paper of Kwiatkowsky et al. [31] used parametrization to represent the stationary and nonstationary variables. The KPSS test is intended to compliment Dickey-Fuller tests and is amongst the most commonly used stationarity tests in applied statistics.

Applying the below listed code, we have been able to obtain the results presented in Table 2.

```
def kpss_test(GDP, **kw):
   statistic, p_value, n_lags, critical_values = kpss(GDP, **kw)
for key, value in critical_values.items():
      print(f'   {key} : {value}')
```

Table 2 reaffirms the findings of Table 1 for the tested time series. The data manipulation involving normalization and log-transformation turned out to be successful and we have managed to make the data stationary.

5.2 Testing the Relationship between Stock Prices and the Economy with an Autoregressive Distributed Lag Model

To determine whether there is a relationship between the BUX composite stock market index and the Hungarian GDP percentage change, we build a model by regressing the GDP percentage change on the past values of BUX. By analyzing the statistical significance of the coefficients corresponding to each lag, we evaluate the null hypothesis, which states that the BUX's effect on the Hungarian GDP is zero and determine the effect of the lagged BUX variable on the dependent GDP variable.

Importing the "statsmodels.formula.api" library in Python, before running the regression, we specify the model:

```
mod_L1_est = smf.ols(formula = 'GDP ~ 1 + lag(Stockmarket, 0) + lag(Stockmarket, 1) + lag(Stockmarket, 2) + lag(Stockmarket, 3) + lag(Stockmarket, 4))', data = data)

mod_L4_fit = mod_L4_est.fit()

print(mod_L4_fit.summary())
```

Listed below are the tables containing the complete OLS regression analysis summary of the paired stock market and GDP time series. The top table of the summary outputs the name of the dependent variable, number of observations, degrees of freedom (Df Residuals), date and time of the program's execution. One of the key outputs in the top table is the R-squared value, which shows what percentage of the change in the dependent variable can be explained by the lagged variable. The adjusted R-squared adds independent variables and measures the reliability of the correlation. The F-statistic shows if the Stock market variable is significant in explaining the variance in the GDP variable. The larger the F-statistic is, the greater its statistical significance. The probability F-statistic should be interpreted as the probability that the null hypothesis, which states that all of the regression coefficients are zero, is true. The closer it is to zero, the better the model is. Both the AIC and Bayesian Information Criteria (BIC) are measures of goodness of fit, the sign of the statistic is irrelevant, as far as the absolute values are considered.

The model is specified in the bottom table. The intercept indicates the result of the equation 1 if all of the constants would be zero and returns only the value of α. Following the intercept, the program outputs the specified lags row by row, and for each of the variables the program further outputs the values of the coefficients, the standard error, the t statistic, the p-value and the 95% confidence interval. The standard error is the measure of heteroscedasticity of the coefficient. The lower the standard error is the better the estimated coefficient, the higher the significance of the coefficient. The p-value denoted as "P>|t|" shows the chance that the stock market has no effect on the GDP. Similarly, to the probability F-statistic, the lower the p-value is, the better the model's fit, the higher the predictive capability of the stock market. The [0.025 and 0.975] column indicates the range within two standard deviations, outside of which the coefficient is unlikely to be found.

Lastly, the bottommost table contains some additional information regarding the model, namely, the omnibus, which describes the skewness and kurtosis of the distribution of residuals, followed by the prob (Omnibus), which indicates the probability the residuals being normally distributed. The Durbin-Watson statistic measures the homoscedasticity of data, ideally a value between 1 and 2.

In case of Hungary the change of BUX log returns is only able to explain around 10.6% of the change in GDP, which is significantly less than the PX's predictive capability. Again, the BUX has also been found to be positively correlated to the GDP, specifically when lagged back up to 1 quarter, as the p-value indicates statistical significance at that specific timeframe. The coefficients at two, three and four lags, therefore, have little statistical significance, and therefore, a lesser relationship to the economy. Considering the Durbin-Watson statistic, the time series have no autocorrelation, as the 2.317 value is close to 2.

We define the Hungarian GDP model as follows:

$$HUGDP = 0.005 + 0.007BUX_t + 0.035BUX_{t-1} - 0.010BUX_{t-2} + 0.0116BUX_{t-3} + 0.0061BUX_{t-4}$$

The conclusions drawn from the coefficient values are the following:

1) An Increase in the percentage change of the Hungarian GDP would result in an immediate increase of the BUX stock index by 0.005, corresponding to 0.5%

2) An increase in the BUX stock index by 3.5% in four months, other things equal

Table 3
OLS regression analysis for BUX and HUGDP

```
                     OLS Regression Results
==============================================================
Dep. Variable:                HUGDP   R-squared:          0.106
Model:                          OLS   Adj. R-squared:     0.059
Method:               Least Squares   F-statistic:        2.232
Date:                  Tue, 23 Nov 2021 Prob (F-statistic):
0.0574
Time:                  12:20:30   Log-Likelihood:      254.99
No. Observations:               100   AIC:              -498.0
Df Residuals:                    94   BIC:              -482.3
Df Model:                         5
Covariance Type:          nonrobust
==============================================================
               coef  std err       t    P>|t| [0.025 0.975]
--------------------------------------------------------------
Intercept      0.0053 0.002      2.617  0.010   0.001 0.009
lag(BUX, 0)    0.0078 0.013      0.614  0.541  -0.017 0.033
lag(BUX, 1)    0.0357 0.012      2.875  0.005  0.011 0.060
lag(BUX, 2)   -0.0107 0.012     -0.855  0.395  -0.035 0.014
lag(BUX, 3)    0.0116 0.012      0.925  0.357  -0.013 0.036
lag(BUX, 4)    0.0061 0.012      0.487  0.627  -0.019 0.031
==============================================================
Omnibus:                102.702   Durbin-Watson:      2.317
Prob(Omnibus):            0.000  Jarque-Bera (JB):   3255.351
Skew:                    -2.889   Prob(JB):              0.00
Kurtosis:                30.348   Cond. No.              6.94
```

Source: Authors research and own compilation

5.3 Johansen Cointegration Test

Extending the research on relationships between stock prices and the economy, we implement a cointegration analysis that sheds light on potential long-run equilibrium relationships between the Hungarian GDP and the BUX composite stock market indexes. Many empirical works omit this step in the Granger causality testing framework, and as of yet, it is unclear why. In this research we justify the importance of cointegration testing through the basic definition of the Granger causality test. In order for variable Y to Granger cause X or vice-versa, it is essential for the time series to be co-integrated.

To perform the Johansen cointegration test in python, we import the “coint_johansen” function from the “statsmodels.tsa.vector_ar.vecm” library. The data are

We specify the statistics in the following lines of code and identify the trend, which in our case is -1, meaning no constant and no deterministic trend:

```
def joh_output(res):
    output = pd.DataFrame([res.lr2,res.lr1],
                    index=['max_eig_stat',"trace_stat"])
    print(output.T,'\n')
    print("Critical values(90%, 95%, 99%) of max_eig_stat\n",res.cvm,'\n')
    print("Critical values(90%, 95%, 99%) of trace_stat\n",res.cvt,'\n')
```

We call the coint_johansen function and run the test :

```
    joh_model1 = coint_johansen(data,-1,2) # k_ar_diff +1 = K
    joh_output(joh_model1)
```

The output of the test detailed below consists of trace statistics and eigenvalue statistics. In the output they are represented in a two-by-two matrix with the variables 0 and 1. The max_eig_stat column shows the maximum eigenvalue score. The eigenvalue statistic shows how strongly co-integrated the series are and how likely their mean reversion is. If the test-statistic (rank of the matrix) is greater than the confidence value at the 95 percent level for the corresponding test, we reject the null hypothesis.

We run the program on the BUX stock market index and the corresponding GDP. It should be remarked, that "cv" stands for critical value in the table below:

Table 4

Johansen cointegration test of BUX log returns and GDP

```
      max_eig_stat  trace_stat
r<0      23.954102   42.137038
r<1      18.182935   18.182935

CV(90%, 95%, 99%) of max_eig_stat
 [[ 9.4748 11.2246 15.0923]
 [ 2.9762  4.1296  6.9406]]

CV(90%, 95%, 99%) of trace_stat
 [[10.4741 12.3212 16.364 ]
 [ 2.9762  4.1296  6.9406]]
```

Source: Author's research. Own compilation

We observe the trace statistic of 42.137, therefore we reject the null hypothesis, meaning that the sum of the eigenvalues is 0. This implies that the BUX and HUGDP time series are co-integrated.

5.4 Granger Causality Test

The null hypothesis under inspection states that the stock indexes do not Granger cause the GDP. The stock market causes GDP, if past values of the Stock market help in predicting the future values of the GDP, therefore we lag the $StockMarket$ variable by 1 quarter.

To test the hypothesis, we import the "grangercausalitytests" from "statsmodels.tsa.stattools" library. We define the number of lags, and run the test as follows:

gc_res = grangercausalitytests(ts_df, 5)

The tables below show the number of lags used in finding causality, the F-test shows if the lagged values of the $StockMarket$ variable improve the forecast of GDP.

Table 5

BUX log returns and Hungarian GDP time series Granger Causality test results

```
Granger Causality
number of lags (no zero) 1
ssr based F test:   F=4.9080   , p=0.0290   , df_denom=99,
df_num=1
ssr based chi2 test:   chi2=5.0567  , p=0.0245  , df=1
likelihood ratio test: chi2=4.9354  , p=0.0263  , df=1
parameter F test:   F=4.9080   , p=0.0290   , df_denom=99,
df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:   F=2.7362   , p=0.0699   , df_denom=96,
df_num=2
ssr based chi2 test:   chi2=5.7575  , p=0.0562  , df=2
likelihood ratio test: chi2=5.5994  , p=0.0608  , df=2
parameter F test:    F=2.7362   , p=0.0699   , df_denom=96,
df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:   F=2.4854   , p=0.0655   , df_denom=93,
df_num=3
ssr based chi2 test:   chi2=8.0176  , p=0.0456  , df=3
likelihood ratio test: chi2=7.7124  , p=0.0523  , df=3
parameter F test:   F=2.4854   , p=0.0655   , df_denom=93,
df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:   F=2.1020   , p=0.0871   , df_denom=90,
df_num=4
```

```
ssr based chi2 test:   chi2=9.2489  , p=0.0552  , df=4
likelihood ratio test: chi2=8.8420  , p=0.0652  , df=4
parameter F test:   F=2.1020   , p=0.0871   , df_denom=90,
df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:   F=2.3424   , p=0.0480   , df_denom=87,
df_num=5
ssr based chi2 test:   chi2=13.1928 , p=0.0216  , df=5
likelihood ratio test: chi2=12.3772 , p=0.0300  , df=5
parameter F test:   F=2.3424   , p=0.0480   , df_denom=87,
df_num=5
```

Source: Author's research. Own compilation

We can observe that the smallest p-value corresponds to the largest F-statistic value – an implication that the BUX precedes the HUGDP. At lag 3 all of the p-values are less than the 0.05 significance level, and therefore we can reject the null hypothesis.

6 Discussion

The goal of this research was to examine if it is possible to predict the Hungarian economy with the BUX index through an intrinsic assertive algorithm involving a stationarity test, a distributed lag analysis, a cointegration test, and finally, and a granger causality test. The lags were chosen based on the AIC, and the results were computed in the Python environment.

We have asserted the pro and counterevidence of stock markets' ability of predicting recessions through an interpretive literature analysis. This allowed us to create a theoretical framework on which we can base the research. The data was retrieved from reliable statistical warehouses and databases. We employed the ADF and the KPSS tests to test whether the data were stationary and applied log-transformation and normalization to make the data mean-reverting. In the next steps with an OLS regression summary in the framework of an autoregressive distributed lag analysis, we have built the models for the individual countries' stock index to GDP relationships. It has been found that the lagged coefficients of BUX are reliable in explaining the changes in the HUGDP.

From the Johansen cointegration test we can assert that there exists a long-run relationship between the BUX composite stock indexes and the Hungarian GDP. From the ADL regression, based on the constructed models, it was determined that past values of Hungarian stock prices do in fact lead Hungarian economic growth, but this does not mean that stock prices Granger cause the economy. The Granger causality tests showed that there exists a causality between the BUX composite stock indexes and the Hungarian GDP.

There are several issues, however, that haven't been addressed in this section. It is possible that the lack of statistical significance in the coefficients can be attributed to the individual GDP time series of V4 countries. The previous statistical alterations of the GDP data, in particular, seasonal adjustment, could have contributed to a less deterministic model. The fact that the GDP was obtained in the country's domestic currency could also have contributed to weak R-squared values. Furthermore, the reason the causal relationship can be attributed to the BUX composite stock index, and the GDP is unclear. What is the role of the forward-looking aspect and the wealth effect on the stock market's relationship with the economy?

Conclusions

The challenge of economic forecasting, has always been in finding those indicators of economic activity, which can predict changes in the macroeconomic environment, before they become evident to the market. While it is highly debated whether the GDP is an accurate measure of a countries' financial and social well-being, it is undoubtable, that it is, currently, the most accurate indicator. That is the main reason, for why it is often used as the primary dependent variable in econometric modelling. The stock markets' identification with the broad economy has also been subject to debate. On one hand, higher corporate profits as a result of increased consumer spending drive share prices higher, on the other hand, speculation, over complication of capital markets and deregulation of financial markets, distances the stock market from the economy. The findings of this study are consistent of the ones conducted by Sayed, Comincioli and Ikoku, who have all found that the stock market is justifiably a leading indicator of the economy, since the growth rate of the BUX Granger-caused the growth rate of the Hungarian economy. The goals of the study have been met and the objectives have been completed. Evidently, Hungarian policy makers must integrate a composite leading indicator, such as the BUX, lagged back one quarter in their early warning system.

For further research, with regards to other leading indicators of capital markets, such as, bond yields on primary and secondary markets, it would be worthwhile considering prediction capabilities of yield curve inversions for forecasting future crises. Investigating yield spreads on corporate and government bonds would also be interesting, from the perspective of investor expectations on future economic conditions.

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